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Ancient Textual Restoration Using Deep Neural Networks: A Literature Review

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***Abstract*— Ancient texts are important because they connect us with ancient civilizations, through which gain cultural, religious, and scientific knowledge, but these texts are often damaged over time due to environmental factors and the method of preservation that affects them, so the task of restoring these texts was one of the necessary tasks for specialists and researchers in ancient sciences. This paper provides an overview of the current state of research in this field. The review would examine the different approaches and methods used, the successes of these methods, and the challenges that need to be addressed in the future. The literature review would also cover the various types of datasets of ancient texts that have been restored using deep neural networks, such as manuscripts, inscriptions, and scrolls, as the different languages and the involved scripts.**

Keywords*— *Ancient texts, deep neural network, image restoration, ancient civilizations, Ancient texts dataset

I. Introduction

The study of ancient writings is essential for acquiring insights into the knowledge, beliefs, and practices of ancient civilizations, which can enrich our understanding of human history and cultural evolution. These texts, which consist of manuscripts, inscriptions, and various other forms of historical documentation, frequently offer insights and data that cannot be gained from other sources. Unfortunately, the deterioration, erosion, and fragmentation of these inscriptions over time have made their restoration and interpretation increasingly challenging [1].

A great deal of information on how people in the past lived and worked. This material is extremely useful for historians who study the past's culture and history. The study of inscriptions, or epigraphy, is one of the most important aspects of Ancient History. Inscriptions provide direct proof of how ancient people thought, lived, and created history, and they were written on hard surfaces such as stone, pottery, and metal [2].

There are numerous ancient original manuscripts and books in museums as well as electronic books on the market that examine the nature of life and culture in the past, and these books contain numerous narratives, images, and other forms [3].

This immense heritage of information about the past inspired the production of artistic works and scholarly studies on ancient civilizations, which enriched our understanding of the past, influenced contemporary culture, and drove technological advances for preserving old writings.

A few of the remaining inscriptions can be read in their entirety and are all present. The epigraphist must then hypothesize how much text is missing; these authors made equal contributions to this book, and what it may have been originally. The term for these hypotheses is "restorations"[4].

These limitations have led to a growing interest in more advanced, automated techniques for ancient textual restoration.

The development of digital humanities has had a significant impact on the study of ancient texts [5].

Increased demand for the conservation and digitization of historical manuscripts has resulted from a growing interest in ancient civilizations. This demand has led to the development of new approaches, such as deep neural networks, for extracting old writings (DNNs). As historians and aficionados strive to uncover the secrets of the past, they are compelled to create more sophisticated and effective techniques for restoring damaged or corroded writings. This technological advancement is advantageous not just for the subject of ancient textual restoration, but also for allied fields such as natural language processing, computer vision, and artificial intelligence [6].

Variability in scripts, languages, and writing styles, insufficient or missing information, which necessitates informed assumptions or extrapolation to fill in the gaps and can make decipherment more difficult.

Because of the lowest number of parameters and focuses more on domain-specific features, Convolutional Neural Networks (CNNs), a form of DNN created specifically for image processing had been used in computer vision applications to overcome these obstacles.

In addition, DNNs may be trained to detect and comprehend a vast array of scripts and languages, enabling the automated decipherment of previously unintelligible writings. This can be accomplished by utilizing recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, which are built for processing sequences and have been widely implemented in natural language processing applications [7].

The rest of this paper is organized as follows: the second section includes the related work. The third section discussed deep learning for text restoration. The fourth section contains the discussion while the final section contains the conclusion.

II. Related Work

In this paper, we explore the exciting intersection of historical preservation and artificial intelligence, delving into the capabilities of deep learning techniques for the restoration and interpretation of ancient texts. Over the centuries, innumerable texts containing invaluable historical, cultural, and linguistic information have suffered damage, leading to significant gaps in our understanding of the past. Recent advancements in deep neural networks present a unique opportunity to address these challenges by automating the restoration process and enhancing our capacity to decipher and reconstruct these precious artifacts.

This section provides a comprehensive overview of the existing literature in the fields of ancient textual restoration, digital humanities, and deep learning.

Using a Convolutional Neural Network, A. El-sawy, and M. Loey devised a method for identifying Arabic handwritten characters (CNN). Due to the intricacy and diversity of the Arabic script, which has 28 letters with varied shapes and forms depending on their position in a word, Arabic handwriting detection is a difficult undertaking. The authors introduced a CNN architecture developed exclusively for Arabic character recognition. They described the creation of a dataset, which includes preprocessing procedures such as image scaling, normalization, and data augmentation to enhance the model's performance and robustness. In terms of accuracy and efficiency, their suggested CNN-based solution for Arabic handwritten character recognition outperforms other approaches previously employed. This study contributed to the field of optical character recognition (OCR) by offering an effective solution based on deep learning for recognizing handwritten Arabic characters [8].

Su et al. [9] suggested a new method for restoring ancient Chinese characters with dual generative adversarial networks (GANs). The authors sought to build a deep learning-based method for restoring and improving the quality of deteriorated photographs of ancient Chinese characters. A generator network for boosting image quality and a discriminator network for evaluating the quality of created images comprise their suggested method. The dual GAN design utilizes both global and local characteristics of the characters, allowing for enhanced performance in character restoration. In addition, the authors present a multi-scale loss function to optimize the restoration process and improve character details. The method is examined using a dataset of degraded images of ancient Chinese characters; the findings confirm the dual GAN approach's usefulness in recovering the characters with high quality and precision.

T. Shen et. al. suggested the Blank Language Model (BLM), a model that creates and fills in blanks dynamically to construct sequences. Which portion of the sequence is expanded and controlled by the blanks. BLM is therefore perfect for a range of text editing and rewriting activities. The starting point for the model can be a single blank line or a partially written text with blank spaces in designated places. It decides iteratively which word to use in a blank and whether to add additional ones before ceasing to generate when there are no more blanks to fill. By applying a lower bound on the marginal data probability, BLM can be trained effectively. BLM considerably exceeds all other baselines on the task of completing missing text snippets in terms of accuracy and fluency [10].

M. A. Souibgui and Y. Kessentini suggest Document Enhancement Generative Adversarial Networks (DE-GAN), an efficient end-to-end system that uses conditional GANs (cGANs) to fix badly damaged document images. the authors showed that DE-GAN can create an improved and high-quality version of the degraded document in a variety of tasks (document cleanup, binarization, deblurring, and watermark removal). Also, using the widely used DIBCO 2013, DIBCO 2017, and H-DIBCO 2018 datasets, their solution consistently outperforms state-of-the-art techniques, demonstrating its capacity to restore a degraded document image to its ideal state [11].

W. Zheng et al.[12] introduce a generative adversarial network-based EA-GAN, which fuses reference instances, and is a two-branch structure character restoration network, to correctly repaired the damaged character, even if the damaged. The up sampling stage's scaled character characteristics and neighborhood data fix the damaged character. An Example Attention structure block may help align the example features and fixed character features and restrict the convolution receptive field. EA-GAN uses the additional example in the Example Attention block to find the right text structure in qualitative and quantitative experiments. PSNR, SSIM, and LPIPS are improved. VGG and AlexNet lowered the LPIPS value by 35.04% and 16.36%, respectively, outperforming current repair methods.

Parker et al. [13] developed a novel method to recover and improve Herculaneum papyri ink. Carbonized by Mount Vesuvius' 79 AD eruption, the papyri are fragile and hard to read due to ink degradation. The authors presented a non-destructive technology employing X-ray phase-contrast tomography (XPCT) and machine learning to disclose invisible ink and increase text readability. XPCT imaging captures high-resolution, 3D papyri images, and machine learning algorithms recognize and segment ink traces from the background to improve visibility. The authors test their method on Herculaneum papyri samples and find that it reveals ink and improves readability.

Nguyen et al. [14] proposed a character attention generative adversarial network (CAGAN) for restoring heavily damaged character patterns in old documents so that OCRs can get better at reading them and archeologists can figure out what they say, the network is based on a U-Net like architecture, and it is trained by a loss function which includes the common adversarial loss as a global loss and a hierarchical character attentive loss as local loss term.

Uzan et al. [15] developed a rotation and reflection-modified PixelCNN to restore letters in ancient Qumran writings. The Dead Sea Scrolls' Qumran texts are important historically and religiously, but their condition has deteriorated, making many letters unreadable or partially visible. To fix text letter orientation, the authors developed PixelCNN to include rotation and reflection operations. They construct a more rotationally invariant model that can handle letter orientations. The PixelCNN predicts missing or damaged letters based on context and restoring text appearance. Using a dataset of Qumran writings, the rotation and reflection modified PixelCNN restores ancient text letters.

Chen, K. et. al. Proposed a CNN with only a single convolution layer. Text lines are segmented using super-pixel labeling, in which each pixel is categorized as a backdrop, main text, adornment, or comment. The input to the categorization is a super-pixel-centered patch. Several well-known datasets, such as the George Washington, St. Gall, and Parzival, have been utilized in experiments. The presented results demonstrate a high degree of precision. For better comprehension, the suggested model is compared to CRF and

Multilayer Perceptron (MLP) as pixel classifiers, yielding correct results. The proposed strategy improves superpixel labeling mean accuracy and Intersection over Union (IU) from 1% to 4%, up to more than 90%, depending on the tested dataset [16].

Pastor-Pellicer, J. Estimated text line Major Body Area (MBA) for segmentation. MBA is the corpus-baseline region. Two classifications are considered. A sliding pane centered on each pixel classifies each pixel as background, text block, or decorative. Pixel tagging distinguishes text. A second CNN monitors a sliding window centered on text blocks to mark MBA pixels. Parzival and St. Gall data sets are used to test the approach. The proposed deep learning method is the only one that consistently outperforms the other compared methods. Non-deep-learning methods include historical page analysis by anisotropic scale-space smoothing, related component identification, and text line segmentation by clustering algorithms. Dynamic Multilayer Perceptron (DMLP) classifier-based text-lines extraction yields equivalent results [17].

Renton, G et. al. [18] modified Deep Fully Convolutional Networks (FCNs) with dilated convolutions. In this study, the input and output sizes are identical, and the network labels pixels even without an explicit sliding window. The FCN is trained to recognize the X-height (distance between the baseline and mean line) of text lines, and its output is comparable to the MBA labeling proposed in [17]. The outcomes are compared to machine learning-based methodologies. The method is quite near to state-of-the-art findings, increasing some of them in terms of Precision, Recall, and F1 score (performances from 88% to almost 95%) and approaching others based on convolutional architectures such as U-net or its variants.

Alaasam, Kurar, and El-Sana used a Siamese network to analyze difficult historical Arabic writings. Layout analysis, detecting, and classifying document regions is essential to document analysis and recognition. Due to their complicated layouts, varied writing styles, and degeneration, historical Arabic manuscripts present particular issues. A Siamese network-based layout analysis tool may successfully capture regional variances in medieval Arabic manuscripts. The Siamese network uses two identical CNN architectures that share weights to translate input regions to a feature space where the distance between feature representations corresponds to region similarity. The proposed method is tested on difficult historical Arabic texts and compared to existing cutting-edge methods. The Siamese network-based layout analysis method for old Arabic manuscripts is accurate and efficient [19].

A. Prusty et al. In this study, the distinction between instance segmentation and semantic segmentation is considered and explained. Using a deep model based on a Mask R-CNN with a ResNet-50 backbone, different text lines in Indic historical documents [16] are identified. Compared to other approaches, a greater number of classes are examined among the object types: Character line segment, Page border, hole, boundary line, Character component, and physical deterioration [20].

Watanabe, K. et. al. Proposed a method for character segmentation consisting of the application of an FCN and a post-processing phase applied to its outputs. The suggested technique has three primary characteristics: it can immediately process input photos including numerous text lines, eliminating the need for text lines segmentation; it is character recognition-independent; and it is robust to fluctuations in character size, character gaps, and overlapping. The task of character segmentation has achieved an accuracy of 95% when tested on actual photographs of Japanese historical handwritten government documents [21].

Ziran et al. trained an initial model to identify common words and hyphens on pages. Convolutional architectures first described for object detection in natural images (Faster R-CNN) are trained to locate words on pages of the Bible printed by Johannes Gutenberg. Using the model prediction, a second model is trained to recognize certain landmark words. The landmark words are common, easily-located words that are utilized to align the image with an erroneous page transcription [22].

Cai et al. work on recognizing old Chinese characters, but they have trouble with things like low image quality and not having enough labeled training samples. The authors suggested a method based on GANs and transfer learning to make it easier to solve these problems. The CNN is the basis for the discriminator, while the the generator is made up of an encoder-decoder based on CNN. To test how well the proposed method (TH-GAN) works, experiments are done on two tasks. The first task is style transfer mapping for multi-font printed traditional Chinese character samples. The second task is transfer learning for historical Chinese character samples by adding samples generated by TH-GAN. The results of the experiments show that the proposed TH-GAN works [23].

N. Shobha Rani et al. suggested repairing text damaged by stain marks, ink seepages, and aging. These issues hinder document improvement. This study solves problems with tri-level semi-adaptive thresholding. Nonetheless, removing the damage that obscures letters is the major objective. The suggested method includes pre- and post-enhancement and three degradation elimination stages. Pseudo-coloring uses local thresholding, while level-wise deterioration elimination uses global thresholding. It removes ink and oil stains off palm leaves and DIBCO documents while retaining hard-to-read text. Our approach eliminated uneven lighting, see-throughs, discoloration, and writing in DIBCO and palm leaf datasets. Benchmark thresholding approaches match the suggested method. It is average F-measure and precision are 65.73 and 93% for DIBCO datasets and 55.24 and 94% for palm leaf datasets [24].

E. Fetaya et. al. the study presents a new approach for restoring fragmentary Babylonian texts using recurrent neural networks (RNNs). The authors train their model on a dataset of cuneiform tablets with missing pieces and show that their method outperforms previous approaches to text restoration. They also demonstrate the potential of their approach to uncover new insights into Babylonian history and culture. The study highlights the importance of machine learning techniques in the field of archaeology and the humanities more broadly [25].

Y. Assael et al. [26] presented a case study on restoring ancient Greek epigraphy using deep learning techniques. The authors used a convolutional neural network (CNN) to recognize and restore damaged characters in inscriptions from ancient Athens. They showed that their method outperforms traditional restoration techniques, and can restore highly degraded text with a high degree of accuracy. The authors also discussed the potential of their approach for advancing research in the field of ancient Greek history and epigraphy. The study demonstrated the potential of deep learning for restoring and analyzing ancient texts and highlights the importance of combining traditional and modern methods in the field of digital humanities.

M. Wadhwani et. al. discussed techniques for text extraction and restoration of old handwritten documents using computer vision and machine learning methods. The authors present an end-to-end pipeline for processing handwritten document images, which includes preprocessing, text localization and segmentation, text recognition, and text restoration. They demonstrate the effectiveness of their approach on a dataset of old Bengali manuscripts and show that their method can accurately extract and restore text from highly degraded documents. The study highlights the potential of computer vision and machine learning techniques for preserving and analyzing historical documents and underscores the importance of developing new methods for the digital preservation of cultural heritage [27].

L. Chen et. al. presents a method for recognizing Japanese ancient text using deep learning techniques. The authors train a convolutional neural network (CNN) to recognize characters in ancient Japanese manuscripts, which often have unique styles and variations compared to modern Japanese. They demonstrate the effectiveness of their approach on a dataset of ancient Japanese documents and show that their method achieves high accuracy even for highly degraded and difficult-to-read text. The authors also discuss the potential of their approach for advancing research in the field of Japanese history and literature. The study highlights the potential of deep learning techniques for analyzing and preserving cultural heritage and underscores the importance of developing new methods for the digital preservation of historical documents [28].

J. Martens proposed a method for generating text using recurrent neural networks (RNNs). The author explains how RNNs can be used to learn the statistical structure of language and generate text that is coherent and grammatically correct. The paper also presents a specific implementation of RNNs, called the long short-term memory (LSTM) network, which is designed to address the problem of vanishing gradients in traditional RNNs. The author demonstrates the effectiveness of their approach on a dataset of Shakespearean text and discusses potential applications for language modeling, machine translation, and other natural language processing tasks. The study highlights the potential of recurrent neural networks for generating new text and advancing research in the field of natural language processing [29]. The summary of related work shown in table I.

TABLE I. SUMMARY OF RELATED WORK.

Study	Method
A. El-sawy, and M. Loey [8]	for identifying Arabic handwritten characters (CNN)
Su et al. [9]	restoring ancient Chinese characters with dual generative adversarial networks (GANs)
T. Shen et. al.[10]	the Blank Language Model (BLM), a model that creates and fills in blanks dynamically to construct sequences
M. A. Souibgui and Y. Kessentin [11]	Document Enhancement Generative Adversarial Networks (DE-GAN), an efficient end-to-end system that uses conditional GANs (cGANs) to fix badly damaged document images
W. Zheng et al.[12]	generative adversarial network-based EA-GAN, which fuses reference instances, and is a two-branch structure character restoration network. to correctly repaired the damaged character, even if the damaged
Parker et al. [13]	X-ray phase-contrast tomography (XPCT) and machine learning to disclose invisible ink and increase text readability
Nguyen et al. [14]	character attention generative adversarial network (CAGAN) for restoring heavily damaged character patterns in old documents so that OCRs can get better at reading them and archeologists can figure out what they say, the network is based on a U-Net like architecture
Uzan et al. [15]	developed a rotation and reflection-modified PixelCNN to restore letters in ancient Qumran writings
Chen, K. et. al.[16]	CNN with only a single convolution layer. Text lines are segmented using super-pixel labeling
Pastor-Pellicer, J.[17]	Estimated text line Major Body Area (MBA) for segmentation with CNN
Renton, G et. al. [18]	modified Deep Fully Convolutional Networks (FCNs) with dilated convolutions
Alaasam, Kurar, and El-Sana [19]	Siamese network to analyze difficult historical Arabic writings two identical CNN architectures
A. Prusty et al.[20]	Using a deep model based on a Mask R-CNN with a ResNet-50 backbone, different text lines in Indic historical documents
Watanabe, K. et. al.[21]	Proposed a method for character segmentation consisting of the application of an FCN and a post-processing phase applied to its outputs
Cai et al. [23]	recognizing old Chinese characters on GANs and transfer learning to make it easier to solve these problems
E. Fetaya et. al.[25]	restoring fragmentary Babylonian texts using recurrent neural networks (RNNs).
Y. Assael et al. [26]	restoring ancient Greek epigraphy using deep learning techniques. The authors used a convolutional neural network (CNN) to recognize and restore damaged characters
M. Wadhwani et. al.[27]	text extraction and restoration of old handwritten documents using computer vision and machine learning methods.
L. Chen et. al.[28]	presents a method for recognizing Japanese ancient text using deep learning techniques. The authors train a convolutional neural network (CNN)
J. Martens[29]	proposed a method for generating text using recurrent neural networks (RNNs).

III. DEEP LEARNING FOR TEXT RESTORATION

In addition, the lack of experts in the ancient language can make it difficult to evaluate the accuracy of the model's outputs. Finally, it is important to remember that deep learning models are not capable of understanding the cultural context in which the language was used, and so their outputs may not always be accurate or useful for researchers

IV. DISCUSSION

Understanding human history, culture, and knowledge is dependent on the restoration and preservation of historic texts. Yet, repairing damaged, faded, or largely obliterated texts has been fraught with difficulties. Previous techniques, such as hand transcription and restoration, were labor-intensive, time-consuming, and susceptible to human mistakes. With the development of deep neural networks (DNNs), academics have been exploring new techniques for restoring old writings, allowing for faster and more precise findings. This literature review seeks to provide a comprehensive analysis of the application of DNNs in the restoration of ancient texts, as well as the important methodologies and achievements in this field.

A. Recognition of Optical Characters (OCR)

OCR is one of the earliest uses of DNNs within the subject of ancient textual restoration. OCR is the process of automatically identifying and recognizing characters in written or printed documents. DNNs, notably convolutional neural networks (CNNs), have been used to enhance the accuracy and performance of OCR systems for ancient manuscripts. To extract text from images, these systems typically employ a combination of image preprocessing, segmentation, and recognition tasks.

B. Picture segmentation

This entails isolating the text from the backdrop and other visual artifacts, which is another essential stage in the restoration procedure. DNNs, especially U-Nets and their variants have been effective at accurately segmenting old manuscripts, even when they are highly damaged and faded.

C. Organic Language Processing (NLP)

Ancient manuscripts have been reconstructed using NLP approaches, such as language modeling and machine translation, to rebuild missing or damaged pieces. In this sense, recurrent neural networks (RNNs) and transformer models, such as BERT and GPT, have been especially useful. Based on the surrounding context and their thorough training in language patterns, these models can anticipate the most probable words or phrases to fill in the gaps.

D. Many kinds of ancient literature exist, including pictures, multispectral images, and 3D scans.

Researchers have investigated the use of DNNs to blend these many data modalities to produce a more complete and accurate representation of text. Using techniques such as data augmentation and transfer learning, the restoration process has been enhanced by integrating data from numerous sources.

E. Despite tremendous progress in the restoration of old texts using DNNs, some obstacles remain.

The restricted availability of labeled data for training these algorithms is one of the major concerns. To overcome this issue, researchers have investigated strategies such as unsupervised learning, semi-supervised learning, and synthetic data generation. Another difficulty is adapting DNNs to various writing styles, scripts, and languages. While certain models have yielded spectacular outcomes for particular languages, they may not perform as well in other circumstances. Future research could concentrate on constructing text-handling models that are more flexible and versatile.

F. Lastly

The interdisciplinary of ancient textual restoration necessitates more collaboration between computer scientists, historians, linguists, and other subject matter experts. This collaboration will ensure that the produced models are suited to the field's particular requirements and obstacles.

G. Dataset

Cleaning strategies are essential in the preprocessing step of machine learning and data analysis jobs. They include techniques and processes for detecting and dealing with mistakes, inconsistencies, missing values, outliers, and other problems in a dataset. The following points will help you understand the significance of dataset-cleaning methods:

- Accurate and reliable analysis
- Improved model performance
- Data consistency

In general, Deep neural networks have revolutionized the field of ancient textual restoration by offering faster, more accurate, and less labor-intensive methods than traditional approaches. By harnessing the power of OCR, image segmentation, NLP, and multimodal data fusion, researchers have made significant strides in restoring and preserving our cultural heritage. Although challenges remain, continued research and interdisciplinary collaboration promise to unlock new insights into the past and ensure that our collective history remains accessible for the coming generations.

V. CONCLUSION

A literature study in this paper has highlighted the considerable advances in ancient textual restoration brought about by the use of deep neural networks. Researchers have solved multiple obstacles that traditional restoration methods faced, such as damaged or missing portions, faded ink, and language limitations, by applying various approaches such as optical character recognition, image segmentation, and natural language processing. These models' development and refining have paved the way for a more accurate and fast restoration procedure, allowing researchers to get a better knowledge of ancient writings and their historical context.

But, there is still space for development, as with any quickly growing pitch. Future research could concentrate on improving deep neural network performance by adding domain-specific knowledge and creating more complicated models that can adapt to varied writing styles and languages. Furthermore, a multidisciplinary collaboration among computer scientists, historians, and linguists will be critical in fine-tuning these technologies to suit the unique needs and challenges of ancient textual restoration. By continuing to investigate the potential of deep neural networks in this subject, also uncover previously unknown insights into the past. The symbiotic relationship between technology and the study of ancient texts will only grow stronger as time goes on, suggesting a brighter and more informed future for the realm of historical scholarship.

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